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Modeling challenges with influence diagrams: Representation issues

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Abstract and Figures

Since their introduction in the mid 70s, influence diagrams have become a de facto standard for representation of Bayesian decision problems. The need to represent complex problems has led to extensions of the influence diagram methodology to increase their representation power. In this paper, we review the representation issues associated with influence diagrams. In particular, we look at the representation of asymmetric decision problems including conditional distribution trees, sequential decision diagrams, and sequential valuation networks. We also examine the issue of representing the sequence of decisions and uncertainties, and how it is done in unconstrained influence diagrams, sequential valuation networks, and sequential influence diagrams. We also analyze the use of continuous chance and decision variables, including continuous conditionally deterministic variables. Finally, we discuss some of the modeling challenges faced in representing decision problems in practice and relevant software.

An influence diagram | A symmetric ID model for the… | An unconstrained ID model for th… | A sequential valuation netwo… | A Gaussian ID for the Consultant'…

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Modeling Challenges with Influence Diagrams: Representation Issues

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Representation Issues

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Key words: Decision-making under uncertainty, influence diagrams, modeling, probabilistic graphic models, sequential decision diagrams, unconstrained influence diagrams, sequential valuation network sequential influence diagrams

1 Introduction

Influence diagrams (IDs) are graphical models for representing and solving complex decision-makir problems based on uncertain information. Nowadays they have become a popular and standard mod eling tool. As pointed out in a recent special issue of the *Decision Analysis* journal devoted to ID these models "command a unique position in the history of graphical models", Pearl (2005). They wer first used in 1973 by the Decision Analysis Group at Stanford Research Institute for a project for th Defense Intelligence Agency. IDs tried to model political conflicts in the Persian Gulf to see whethe more intelligence resources should be allocated and they also tried to measure the value of informatic produced by the Agency. As chronicled by themselves in Howard et al. (2006), Miller invented a ne

graphical convention that we now call ID, Howard coined the term "influence diagram" and the firs resulting (classified) paper on IDs was North et al. (1974). But it is Howard and Matheson's pape Howard and Matheson (1984), reprinted in Howard and Matheson (2005b), what is considered to cor

tain the invention of IDs and to be the pioneering paper. Other interesting details of the evolutic and application of IDs since their inception may be found in a retrospective, Howard and Mathesc (2005a).

IDs are directed acyclic graphs that may be seen as Bayesian networks augmented with decision ar value nodes. Therefore, there are three types of nodes: (1) decision nodes (rectangular) representir decisions to be made; (2) chance nodes (oval or elliptical) representing uncertainties modelled b probability distributions; and (3) value nodes (diamond-shaped) without children (direct successors representing the (expected) utilities that model decision-maker's preferences. The arcs have differer meanings depending upon which node they are directed to: the arcs to chance nodes or the value nod indicate probabilistic dependence and functional dependence, respectively, while the arcs pointing a a decision node indicate the information known at the time of making that decision. The former ar called *conditional* arcs while the latter are called *informational*.

At the qualitative (or graphical) level, the ID has a requirement that there must be a directe path comprising all decision nodes. It ensures that the ID defines a temporal sequence (total orde of decisions and it is called the *sequencing constraint*. As a consequence, IDs have the "*no-forgettin* property: the decision maker remembers the past observations and decisions. In contrast, the transitiv closure of the precedence binary relation induced by the informational arcs is a partial order on th set of all decision and chance nodes. Therefore, the information constraints represented by these ar may not specify a complete order. From a semantic viewpoint, it means that the decision-maker ma not impose constraints regarding which of two or more chance nodes must precede the others in th decision-making process. For example, after deciding the admission of a patient into a hospital, ther will be no constraints concerning which of the uncertainties cost of stay and risks of being admitte (infections, contagions,...) is the first to occur.

At the quantitative level, an ID specifies the domains of all decision and chance nodes: the li of alternatives for each decision variable and the state space Ω_X of each chance variable X. Als a conditional probability table is attached to each chance node consisting of conditional probabilit distributions, one for each state of its parents (direct predecessors), and a real-valued function, th utility function, is defined over the states of a value node's parents. Probabilities and utilities represer beliefs and preferences, respectively, of the decision maker. When a problem has a utility function tha factorizes additively, each of the additive factors is represented as a value node.

Figure 1 shows an example of the graphical part of an ID. D_1, D_2 are decisions, A, C, R are rando

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... Besides a practical guide to causal discovery (Malinsky and Danks 2018a), there have been papers written about the construction of influence diagrams along with utilities (Bielza et al. 2010) and about representation restrictions imposed by influence diagrams (Bielza et al. 2009). To the best of our knowledge, our work is the first to address the causal gametheoretical models from a practical point of view. ...

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Graham Rand

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